A Generative Adversarial Gated Recurrent Network for Power Disaggregation & Consumption Awareness

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Abstract

Separating the household aggregated power signal into its additive sub-components is called energy (power) disaggregation or Non-Intrusive Load Monitoring. NILM can play an instrumental role as a driver towards consumer energy consumption awareness and behavioral change. In this paper, we propose EnerGAN++, a model based on GANs for robust energy disaggregation. We propose a unified autoencoder (AE) and GAN architecture, in which the AE achieves a non-linear power signal source separation. The discriminator performs sequence classification, using a recurrent CNN to handle the temporal dynamics of an appliance energy consumption time series. Experimental results indicate the proposed method's superiority compared to the current state of the art.

1 Introduction

Raising awareness of individuals on environmental protection and sustainability, is prerequisite to set climate policies, responses or solutions to climate change at global scale (1). There are various ways that householders could contribute to sustainable living. One of them is by reducing their energy consumption. To this end, a change of energy related behavior in the household is required. First, consumers need to become aware of their energy consumption. However, end-consumers often lack knowledge about potential energy savings, existing policy measures and relevant technologies. Most household consumers are usually aware of general information related to their consumption through monthly electricity bills. Nonetheless, the information about energy consumption is not translated into good practices and tailored advice for energy saving.

Non-Intrusive Load Monitoring (NILM) uses the aggregate power signal of a household as input to estimate the extent to which each appliance contributes to the aggregate energy consumption signal. Thus, NILM algorithms can be considered as an efficient and cost effective framework for energy consumption awareness, especially given the fact that installing smart plugs in households to provide a fully personalized solution is not a cost-effective alternative. The goal of the work at hand is to propose an efficient framework for NILM that can be applied to enhance awareness on the energy consumption behavior of consumers in the household and therefore guide them towards a prudent and rational utilization of energy resources.

A brief literature review on NILM methods reveals that deep learning techniques have been applied to low frequency NILM since 2015 (2). Recurrent Neural Netowrks (RNN) and their variants, such as LSTMs and GRUs have been primarily used, as they are effective with 1D time series data. Relevant studies have been carried out in the past (3), (2), (4). Other works include a Bayesian

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optimized bidirectional LSTM model for NILM (5), and a context-aware LSTM model adaptable to external environmental conditions (6). Some works (7) propose a sequence to point CNN architecture, underscoring the importance of sliding windows to handle long-term timeseries. Additionally, seq2seq architectures (8) as well as denoising autoencoders (9) have also been proposed.

2 Problem formulation and paper contribution

Measuring consumption per appliance can be effected with smart plugs, which is however an economically ineffective solution. For this reason, NILM methods can be applied to decompose the total power consumption of a household into individual appliance power signal components without prior existence of smart-plug equipment.

At a discrete time index t, we assume $\tilde{p}(t)$ the noisy aggregate measured energy signal for the whole household under study. Signal $\tilde{p}(t)$ is the sum of the individual appliances' power consumption $p_j(t)$ plus an additional noise $\epsilon(t)$. Thus, in a NILM framework (10), we express the total power consumption $\tilde{p}(t)$ as: $\tilde{p}(t) = \sum_{m=1}^{M} p_m(t) + \epsilon(t)$. Variable m refers to the m-th out of M available appliances. Here, we need a robust to noise model able to separate the total noisy power measurements $\tilde{p}(t)$ into the individual -free of noise- appliance source signals $p_m(t)$. The problem is to calculate the best estimates $\hat{p}_m(t)$ of the appliance power consumption, given the noisy $\tilde{p}(t)$ values.

NILM methods often look at the problem as decomposing a mixture signal into individual appliance signals and formulate the task as an optimization problem. Traditional generative models such as independent component analysis (ICA) (11) and non-negative matrix factorization (12) have been proposed to solve the NILM problem. However, it would be interesting to replace the linear ICA model with an alternative model to capture the non-linearities in energy data consumption signals.

In this paper, we propose EnerGAN++, a GAN-based approach that employs a combined convolutional layer with recurrent GRU unit which can model the long-range dependent and recurrent behaviors of appliances' data consumption. In this way, the performance and robustness of NILM modelling is increased in the cases that noisy aggregate signals are used as input triggers and abrupt changes in the appliance energy distributions are encountered.

3 The proposed EnerGAN++ Model: Generator and Discriminator

The Generator: The NILM framework implies the need for a network trained not only to reproduce the distribution of the power signal of an appliance but also to know its exact operation and consumption at a given time instance t. This can be achieved by using the aggregate signal $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ over a time window of T duration as input trigger to EnerGAN++ (see Fig. 3). Signal $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ is considered as a noise trigger since it is the summation of independent energy consumption signals of the appliances. In addition, during training, the ground truth data of the m-th appliance $\{p_{m,t}^{label}\}_{t=t}^{t=t+T}$ over a time window of T duration is considered to initiate the EnerGAN++ generator to simulate the real energy consumption data of the m-th appliance. We denote by $\mathcal{I}_{train}$ the input trigger vector of the $\mathcal{G}_{EnerGAN++}(\cdot)$ generator during the training phase: $\mathcal{I}_{train} \equiv \left[\{\tilde{p}_t\}_{t=t}^{t=t+T} \; \{p_{m,t}^{label}\}_{t=t}^{t=t+T}\right]^T$. To handle the aggregate signal $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ and the ground truth labels of $\{p_{m,t}^{label}\}_{t=t}^{t=t+T}$ as input trigger of EnerGAN++, an encoder layer is added prior to the decoder. This generates a compressed noise signal z_m (by encoding the input vector signal of $\mathcal{I}_{train}$) which is used as input trigger of the decoder of the generator to produce a real appliance energy consumption time series $\mathcal{G}(z_m)$ for the m-th appliance. Thus, the pipeline of the generator during the *training phase* is the following:

$$\mathcal{I}_{train} \rightarrow Encoder\left(\mathcal{I}_{train}\right) \rightarrow z_m \rightarrow Decoder\left(z_m\right) \rightarrow \mathcal{G}_{EnerGAN++}(z_m) \tag{1}$$

Eq. (1) means that the input signal $\mathcal{I}_{train} \equiv \left[\{\tilde{p}_t\}_{t=t}^{t=t+T} \; \{p_{m,t}^{label}\}_{t=t}^{t=t+T}\right]^T$ is transformed (compressed) to a latent noise trigger z_m, through a convolutional encoder and then, the noise signal z_m is decompressed to generate a signal $\mathcal{G}_{EnerGAN++}(z_m)$ that resembles the real energy consumption of the m-th appliance. The encoder with convolutional layers, is forced to be an inverted version of the decoder (with transposed convolutional layers), where corresponding layers perform opposite mappings and share parameters (13). The model tries to minimize the difference between the $\{\hat{p}_{m,t}^{\mathcal{G}}\}_{t=t}^{t=t+T}$ sequence values and the actual sequence values $\{p_{m,t}^{label}\}_{t=t}^{t=t+T}$, generating data sequences $\mathcal{G}_{EnerGAN++}(z_m)$ that confuse the discriminator $\mathcal{D}$.

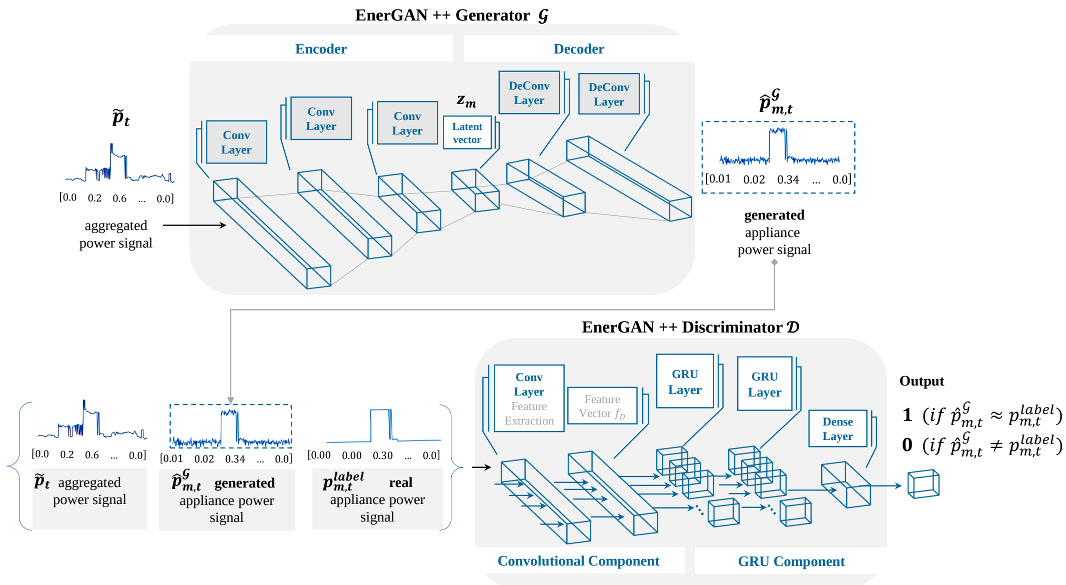

Figure 1: The proposed architecture. The generator is a convolutional AE and has the noisy version of the aggregated power signal as input. The discriminator is a long-term convolutional recurrent network for sequence classification, and is conditioned with the aggregated power signal.

During *the testing phase*, the generator $\mathcal{G}_{EnerGAN++}(\cdot)$ receives as input only the aggregate signal $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ and not the appliance ground truth data of $\{p^{label}_{m,t}\}_{t=t}^{t=t+T}$ since it has been learned during the training phase to produce almost identical energy consumption time series of the m-th appliance. Thus, the pipeline of the EnerGAN++ generator $\mathcal{G}_{EnerGAN++}(\cdot)$ during *the testing phase* is:

$$\{\tilde{p}_t\}_{t=t}^{t=t+T} \rightarrow Encoder\left(\{\tilde{p}_t\}_{t=t}^{t=t+T}\right) \rightarrow \hat{z}_m \rightarrow Decoder\left(\hat{z}_m\right) \rightarrow \mathcal{G}_{EnerGAN++}(\hat{z}_m) \quad (2)$$

The output of the generator during the testing phase approximates its output during training since the ground truth data of the m-th appliance are available only during training. Therefore, we have that $\mathcal{G}_{EnerGAN++}(\hat{z}_m) \approx \mathcal{G}_{EnerGAN++}(z_m)$, meaning that the produced data time series by the generator $\{\hat{p}^{\mathcal{G}}_{m,t}\}_{t=t}^{t=t+T}$ is very close to the labeled data of $\{p^{label}_{m,t}\}_{t=t}^{t=t+T}$

The Discriminator: In the EnerGAN++ model, a combined CNN enriched - GRU classifier is adopted as the discriminator unit. GRU networks are appropriate for modelling the temporal auto-regressive properties of a time series. However, GRU structures cannot extract features from the input data in a way to optimize the overall classification performance. For this reason, in this paper, we adopt a combined approach by introducing a CNN model (14) prior to the GRU framework. The combination of CNN as an efficient feature extractor with the GRU model, is capable of representing, synthesizing and therefore distinguishing the temporal dynamic nature of the power sequence signals. The proposed discriminator has two main components: *the convolutional* layer and the *GRU* unit. The convolutional layer transforms the input signal to a reliable feature vector $f_{\mathcal{D}}(t)$, while the GRU unit performs the discrimination. As input signal the generated power signal $\mathcal{G}_{EnerGAN++}(\hat{z}_m)$ of the m-th appliance is used. In addition, the labeled training samples of the respective appliance $\{p^{label}_{m,t}\}_{t=t}^{t=t+T}$ and the aggregate measurements $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ are used as input triggers for classification comparisons. Initially, the input vector of the discriminator, i.e. the data produced by the generator $\{\hat{p}^{\mathcal{G}}_{m,t}\}_{t=t}^{t=t+T}$, the real labelled data $\{p^{label}_{m,t}\}_{t=t}^{t=t+T}$ and the aggregate measurements $\{\tilde{p}_t\}_{t=t}^{t=t+T}$ are fed as inputs to a CNN structure with the main purpose of transforming them into optimized feature maps of $f_{\mathcal{D}}(t)$:

$$f_{\mathcal{D}}(t) \sim Conv_{\mathcal{D}_{EnerGAN++}}\left(\mathcal{I}_{input}\right) \text{with } \mathcal{I}_{input} = \left[\{p^{label}_{m,t}\}_{t=t}^{t=t+T}, \{\hat{p}^{\mathcal{G}}_{m,t}\}_{t=t}^{t=t+T}, \{\tilde{p}_t\}_{t=t}^{t=t+T}\right]^T$$

The features $f_{\mathcal{D}}(t)$ at time instance t are fed to the GRU trained to distinguish the fake sequence produced by $\mathcal{G}_{EnerGAN++}$ from the real one (available in the training set). Therefore:

$$\mathcal{D}_{EnerGAN++} \equiv GRU\left(f_{\mathcal{D}}(t)\right) = \{\, 1 \text{ if } \{\hat{p}^{\mathcal{G}}_{m,t}\}_t^{t+T} \approx \{p^{label}_{m,t}\}_t^{t+T} 0\text{if } \{\hat{p}^{\mathcal{G}}_{m,t}\}_t^{t+T} \neq \{p^{label}_{m,t}\}_t^{t+T}\}$$

Table 1: MAE Performance metric for nine appliances of the AMPds and REFIT datasets.

	Wash. Dr.	H. Pump	Oven	Dish	Kettle	Micro	Toast	Tum. Dr.	Wash
Proposed	17.7	**80.1**	**8.1**	**20.3**	**7.8**	**8.3**	**2.2**	**16.9**	**7.3**
BabiLSTM (5)	**10.0**	88.2	17.6	29.2	41.2	15.2	12.8	48.7	17.6
DAE (2)	37.3	55.6	19.2	25.4	9.1	12.2	8.3	32.9	13.4
seq2seq CNN (8)	15.4	107.1	67.5	34.9	19.8	14.8	15.0	42.5	27.0
LSTM (4)	90.2	154.9	57.6	102.1	41.1	15.9	26.7	87.8	31.8
FHMM (15)	129.5	121.6	49.3	147.7	40.8	77.3	32.4	91.5	177.0
CO (15)	120.1	249.3	267.1	138.8	40.6	51.8	35.6	91.9	210.9

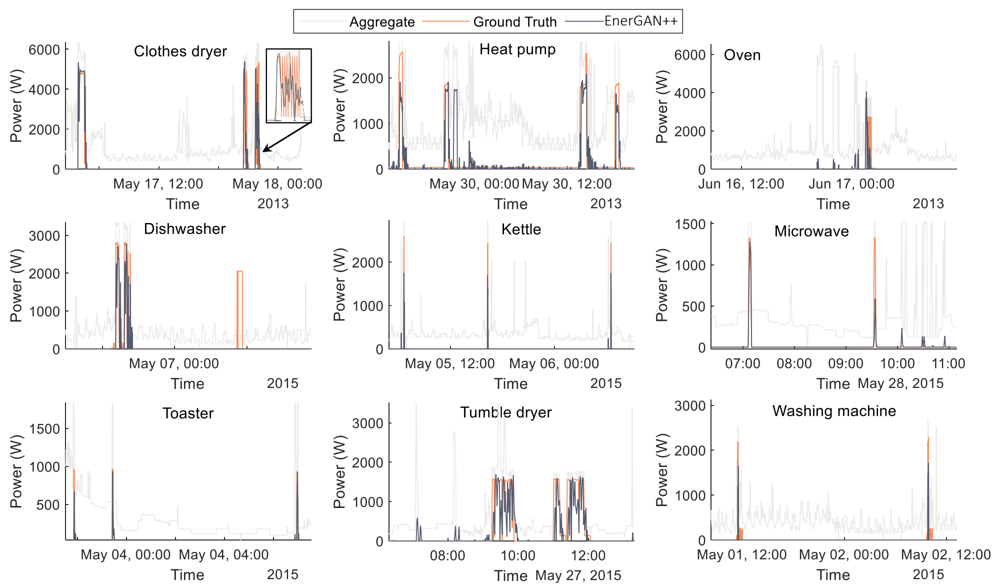

Figure 2: Comparison of the EnerGAN++ method (purple line) with ground truth data (in orange).

4 Experimental Evaluation

The evaluation has been conducted on nine appliances from AMPds (16) and REFIT (17) datasets, which provide aggregate power measurements of a house and sub-metered readings (smart plugs) from individual appliances. Table 1 shows the Mean Absolute Error (MAE) attained by our model and other state of the art methods. In most cases, EnerGAN++ attains the lowest MAE, with the exception of the clothes dryer appliance, where MAE seems to be higher. This could be due to the "jagged edges" appearing in clothes dryer appliance pattern, that are successfully captured by the bidirectional-LSTM. Fig. 2 shows the aggregate signal (grey line), the generated power signal from our model (purple line) and the ground truth data (orange). The operation of each appliance is detected at an adequate level. In Fig. 2, the generated timeseries of power data are identical with the actual operation (ground truth) of clothes dryer, oven, kettle, microwave, toaster, tumble dryer and washing machine appliances. However, during the snapshot in time in Fig. 2, for the heat pump, a false positive appeared, since the appliance is detected in operation five times, whereas it is actually ON only 4 times. On the contrary, a false negative is detected, at first, for the dishwasher, but actually the orange undetected signal for this case indicates noise and not actual presence of the dishwasher.

5 Conclusions

NILM is a useful tool for providing consumers with personalized information regarding their energy consumption. In this paper we propose a novel GAN-based approach for NILM, with promising results, that could be applied as the basis technology in a recommendation engine system guiding consumers towards behavioral change and energy waste reduction.

References

[1] David Rolnick, Priya L Donti, Lynn H Kaack, Kelly Kochanski, Alexandre Lacoste, Kris Sankaran, Andrew Slavin Ross, Nikola Milojevic-Dupont, Natasha Jaques, Anna Waldman-Brown, et al., "Tackling climate change with machine learning," *arXiv preprint arXiv:1906.05433*, 2019.

[2] J. Kelly and W. Knottenbelt, "Neural nilm: Deep neural networks applied to energy disaggregation," in *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, 2015, pp. 55–64.

[3] D. Murray, L. Stankovic, V. Stankovic, S. Lulic, and S. Sladojevic, "Transferability of neural network approaches for low-rate energy disaggregation," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 8330–8334.

[4] J. Kim, T. Le, and H. Kim, "Nonintrusive load monitoring based on advanced deep learning and novel signature," *Computational intelligence and neuroscience*, vol. 2017, 2017.

[5] M. Kaselimi, N. Doulamis, A. Doulamis, A. Voulodimos, and E. Protopapadakis, "Bayesian-optimized bidirectional lstm regression model for non-intrusive load monitoring," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 2747–2751.

[6] M. Kaselimi, N. Doulamis, A. Voulodimos, E. Protopapadakis, and A. Doulamis, "Context aware energy disaggregation using adaptive bidirectional lstm models," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3054–3067, 2020.

[7] C. Zhang, M. Zhong, Z. Wang, N. Goddard, and C. Sutton, "Sequence-to-point learning with neural networks for non-intrusive load monitoring," in *Thirty-second AAAI conference on artificial intelligence*, 2018.

[8] K. Chen, Q. Wang, Z. He, K. Chen, J. Hu, and J. He, "Convolutional sequence to sequence non-intrusive load monitoring," *The Journal of Engineering*, vol. 2018, no. 17, pp. 1860–1864, 2018.

[9] R. Bonfigli, A. Felicetti, E. Principi, M. Fagiani, S. Squartini, and F. Piazza, "Denoising autoencoders for non-intrusive load monitoring: improvements and comparative evaluation," *Energy and Buildings*, vol. 158, pp. 1461–1474, 2018.

[10] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.

[11] Y. Zhu and S. Lu, "Load profile disaggregation by blind source separation: A wavelets-assisted independent component analysis approach," in *2014 IEEE PES General Meeting| Conference & Exposition*. IEEE, 2014, pp. 1–5.

[12] A. Rahimpour, H. Qi, D. Fugate, and T. Kuruganti, "Non-intrusive energy disaggregation using non-negative matrix factorization with sum-to-k constraint," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4430–4441, 2017.

[13] Y. Teng and A. Choromanska, "Invertible autoencoder for domain adaptation," *Computation*, vol. 7, no. 2, pp. 20, 2019.

[14] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep learning for computer vision: A brief review," *Computational intelligence and neuroscience*, vol. 2018, 2018.

[15] N. Batra, J. Kelly, O. Parson, H. Dutta, W. Knottenbelt, A. Rogers, A. Singh, and M. Srivastava, "Nilmtk: an open source toolkit for non-intrusive load monitoring," in *Proceedings of the 5th international conference on Future energy systems*, 2014, pp. 265–276.

[16] S. Makonin, F. Popowich, L. Bartram, B. Gill, and I. Bajić, "Ampds: A public dataset for load disaggregation and eco-feedback research," in *2013 IEEE Electrical Power & Energy Conference*. IEEE, 2013, pp. 1–6.

[17] D. Murray, L. Stankovic, and V. Stankovic, "An electrical load measurements dataset of united kingdom households from a two-year longitudinal study," *Scientific data*, vol. 4, no. 1, pp. 1–12, 2017.